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Temporal discounting does not influence Body Mass Index

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Abstract

The prevalence of obesity has driven searches for cognitive or behavioural economic factors related to Body Mass Index (BMI). One candidate is delay discounting: those who prefer smaller sooner rewards over larger but later rewards are hypothesised to have higher BMI. The findings in the literature are mixed however, with meta analyses suggesting only a very small correlation between discounting and BMI. Here we present novel empirical data ($N = 381$) and Bayesian analyses which suggest no such relationship between discounting of either monetary or weight loss rewards and BMI. We also find evidence against our novel proposal that discounting moderates the rate of BMI gain over time. We also present our data in the context of a random effects Bayesian meta-analytical result which does suggest the presence of a small correlation overall. The strength of the correlation is so weak (2.25% shared variance) that its practical significance may be minor to non existent. However because we found decisive evidence for unaccounted for study-level variance, due to study heterogeneity, we argue that we should treat such meta-analytic correlations with extreme caution. While the relationship between discounting and health outcomes such as BMI remain theoretically appealing, our empirical and meta-analytic results suggest we should be cautious in inferring a correlational, let alone a causal, role for discounting processes in driving BMI or moderating BMI gain with age.

Keywords: Temporal discounting, delay discounting, inter-temporal choice, Body Mass Index, obesity, underweight.

1 Introduction

There has been much interest in understanding the behavioural phenotype which influences an individual's susceptibility to weight gain in obesogenic environments (Dalton, Finlayson, Esdaile, & King, 2013). One candidate behaviour is that of delay discounting – the degree to which one discounts the future rewards determines the relative preference between smaller sooner or larger later rewards. The kind of valuation between sooner versus later rewards captured by discounting has been linked to certain facets of the broader impulsivity construct (Dougherty, Mathias, Marsh, & Jagar, 2005; Green & Myerson, 2013; Meda et al., 2009) and implicated

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in addiction which relies upon impulse control (Bickel et al., 2012a; Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012b; MacKillop et al., 2012). Channelling the 'obesity as food addiction' model (eg. Davis et al., 2011), obesity is also associated with decision making processes that involve elements of impulsivity in consequential trade-offs (Davis, Patte, Curtis, & Reid, 2010; Epstein, Salvy, Carr, Dearing, & Bickel, 2010), leading to the question of whether Body Mass Index (BMI) may be driven by temporal discounting.

Four recent meta analyses suggest there is a small overall relationship between discounting and BMI, and all note considerable study heterogeneity. McClelland et al. (2016) conducted a meta-analysis exploring temporal discounting and obesity, finding mixed results; 44% of studies reported higher discount rates in obesity , 39% of studies reported no difference in discounting between obese individuals and healthy controls , and 2 studies found reduced discounting in obesity. Amlung, Petker, Jackson, Balodis, and MacKillop (2016) also conducted a meta-analysis, focusing on BMI and the discounting of money and food rewards. Their findings show a more robust relationship for case-controlled designs over correlational designs, but argue for a medium effect size in the association between BMI and discounting, and argue that discounting may be a valid therapeutic target. Emery and Levine (2017) conducted a meta-analysis which explored the broader notion of impulsivity (rather than discounting specifically) and BMI, strongly arguing that the relationships found in various studies depend upon how impulsivity is measured, and which specific domain of impulsivity is being explored. Tang, Chrzanowski-Smith, Hutchinson, Kee, and Hunter (2018) also explored money and food-reward discounting in relation to obesity, investigating the mixed literature from a methodological perspective. They argue for an association between discounting and BMI – more studies with best-practice methods and larger samples found positive correlations (15 of 27; 55.6%) than those using non-best practice methods (14 of 34; 41.2%). However, given sizeable proportions of studies not finding an effect regardless of their practices, then this is not clear-cut evidence for an effect.

Taken together, this could be seen as solid evidence for a low to medium effect size of discounting on BMI. But all meta analyses note high heterogeneity of studies in a number of ways. Firstly, most studies examine discounting of monetary rewards such as the fixed Monetary Choice Questionnaire (MCQ; Kirby, 2009) but some studies use adaptive methods. Secondly, some studies examine discounting of money, and others discounting of food rewards – given that different rewards are discounted at different rates (e.g. Odum, Baumann, & Rimington, 2006) this is also likely to contribute to the varied findings. Some studies report discount rates, others log discount rates, and others the Area Under Curve measure (Myerson, Green, & Warusawitharana, 2001). Third, studies do not all have the same classification criteria for obese participants. Fourth, more studies reported positive correlations between discounting and BMI when they used food rewards (e.g. Manwaring, Green, Myerson, Strube, & Wilfley, 2011) as opposed to monetary rewards (Amlung et al., 2016; Emery & Levine, 2017; Tang et al., 2018). Most studies use monetary rewards when measuring discounting as it is considered the most universally valued reward, however a concern arises from the assumption that monetary discounting is representative of all temporal preferences. Therefore, an important point is to think about what precise discounting construct is most likely to be related to BMI? How far can we truly suggest that our decisions regarding weight-loss are related to how we value generic monetary reward?

These concerns were at the heart of research by Lim and Bruce (2015) who examined discounting of weight-loss achievements – those who favoured smaller but more immediate weight loss may choose counter-productive dieting strategies (Karim, 2015; Neumark-Sztainer, Wall, Haines, Story, & Eisenberg, 2007) or high BMI might lead to greater desire for immediate weight loss (Hill, 2004). They created the Weight-Loss Choice Questionnaire (WCQ), adapting the MCQ by simply translating monetary rewards into weight-loss achievements. They found that log discount rates for weight loss and monetary rewards were correlated (r = .33, $p < 0.05$, n =

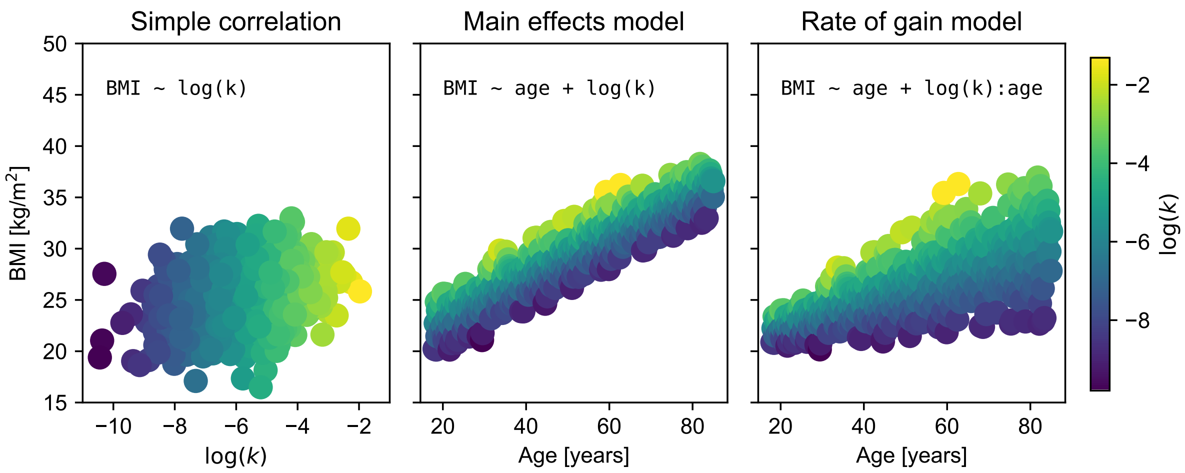

Figure 1: Schematic demonstrations of some possible relationships between discount rates and BMI. The simple correlation approach (left) is taken in the majority of previous studies but ignores the known relationship between age and BMI. A main effects model (middle) may potentially find a main effect of discount rate in addition to age. The rate of gain model (right) may find that discount rates moderate the rate of BMI gain with age. Text captions provide corresponding linear modelling syntax. The discount rate k is in units of days^{-1}, but $\log(k)$ is a unit-less quantity.

42), suggesting approximately 10% shared variance between these measures. However neither of these discount rates was significantly correlated with BMI, something they attributed to their small sample size, rather than the absence of a correlation.

We propose that looking for a correlation between discount rates and BMI (e.g. Figure 1, left) might be a good first step, but the insight this approach can provide is potentially limited. In a longitudinal study of 1,988 adults spanning 50 years, Sutin and Ferrucci (2011) found on average that BMI increases with age. They also found that participants scoring in the top 10% of impulsivity facets of the Revised NEO Personality Inventory (Costa & McCrae, 2013) weighed on average 11 kg more than those in the bottom 10%. Given that BMI changes over time, it might be over simplistic to suspect that a participants discount rate determines their absolute BMI. So a superior approach would be to evaluate the strength of a main effect of discount rate in addition to a main effect of age (e.g. Figure 1, middle). If there were main effects of age and discount rate, this model would state that 'BMI increases with age, but people of a given age who discount at a higher rate have higher BMI'. We propose a further model that discount rates are a behavioural phenotype moderating the susceptibility of weight gain with age (e.g. Figure 1, right). This is a process model, postulating that discount rates moderate the rate of weight gain with age. This idea is consistent with the finding that children with higher self-control stay leaner in the transition to adolescence (Duckworth, Tsukayama, & Geier, 2010). In this paper, we quantitatively evaluate each of these 3 proposals (Figure 1) using Bayesian methods, based upon discounting of monetary or weight loss rewards.

This study sought to extend our knowledge of whether and how discounting processes are related to the real world health outcome of BMI. Firstly, we extend the work of Lim and Bruce (2015) by exploring whether discount rates for money or weight loss are related to BMI with 9 times the number of participants. Using Bayesian analyses we find evidence against there being a correlation between either discount rate and BMI. Secondly we test, and find evidence against, the hypothesis that discount rates drive behaviours that moderate the rate of BMI change over time. Third, we explore whether discounting may relate to one's subjectively evaluated BMI via the Stunkard figure rating scale (SFRS; Stunkard, Sørensen, & Schulsinger, 1983). Fourth, we present Bayesian meta-analytic results which suggest that there *is* a correlation between discounting and BMI. Fifth, we offer some rationalisation – our meta-analytical results clearly show correlations reported in the literature are not measuring the same underlying quantity and should therefore be interpreted with caution. We point to ways forward for the field.

2 Methods

2.1 Participants

This study used a questionnaire design reviewed and approved by The University of Dundee Ethics Committee. Participants were recruited using volunteer sampling methods by distributing the questionnaire online. All submissions were completely anonymous, open to anyone aged 18 or over, and a total of 408 submissions were received. Because of our recruitment methods we believe the majority of participants responding will have been from the UK, but that some of our online efforts at participant recruitment will have achieved a broader reach amongst English speaking countries or participants.

While the respondents were all unpaid volunteers, and therefore had some level of intrinsic motivation to complete the questionnaire accurately, we used fairly strict exclusion criteria. 22 participants were removed for missing or incorrect responses or for being under 18. One participant who did not disclose their sex assigned at birth was excluded. We calculated the proportion of responses correctly predicted by hyperbolic discounting and the estimated discount rates given the data. A threshold of 70% responses was set, resulting in 1 participant being excluded on the basis of the MCQ, and 3 participants on the basis of WCQ. The resulting median responses predicted were 92.6% and 88.9% for the MCQ and WCQ scores, respectively. Participants who always chose the delayed reward were not excluded as this is most likely due to the limited range of discount rates that the MCQ is sensitive to, rather than aberrant responding.

This resulted in a final dataset of $N = 381$ (242 female, 139 male), with 257 reporting they were interested in weight loss. All measures were taken for all participants, except for the WCQ which was only measured for those reporting interest in weight loss.

2.2 Questionnaire

The questionnaire asked for participants' age, sex (assigned at birth), height and weight. Height and weight units were manually converted to meters and kilograms, respectively. Body Mass Index was calculated as weight/height^2 resulting in BMI in units of kg/m^2. Participants indicated if they were interested in losing weight or not, and were asked to write how much if they selected yes. Dieting background/behaviour was assessed by choice of one of the following statements: I have never dieted; I have dieted in the past; I am currently dieting; I hope to diet in the future. Participants then completed the MCQ, the WCQ, and the SFRS (all outlined below).

2.3 Stunkard Figure Rating Scale (SFRS)

Participant's perceived body size was measured using the Stunkard Figure Rating Scale (SFRS) (Stunkard et al., 1983), which consists of 9 images of male and female body line-drawings that gradually increase in size. Each figure is based upon an average size and shape of persons within a set of BMI scores (e.g. the drawings that correspond with the number 5 are recognised as being within the 25 to 28 BMI score range). This measure was used to help provide an alternative to BMI scores, as multiple studies note how BMI weight categories can be too rigid and may not account for a person's overall health (Amlung et al., 2016; World Health Organization, 2000, 2011).

2.4 Analyses

Many of the analyses presented in the Results section were conducted using JASP (JASP Team, 2019). Evaluation of the 'discounting as moderator of rate of BMI gain' hypothesis, and the Bayesian meta analyses were conducted using Python and the PyMC3 package (Salvatier, Wiecki, & Fonnesbeck, 2016). All data and analyses are available in the Online Supplementary Material, which also includes additional descriptive statistics and analyses conducted in the R language. Further advanced scoring and analysis methods are described in subsequent sections.

2.5 Discounting measures

Participants answered Kirby's Monetary Choice Questionnaire, a popular measure of 27 questions for delay discounting of monetary rewards (Kirby, 2009). It asks participants to select if they prefer between smaller immediate and larger later monetary rewards. For example – "Would you prefer to have (A) £55 immediately, or (B) £75 in 61 days?"

Following Lim and Bruce (2015), participants were only asked to complete the Weight-Loss Choice Questionnaire (WCQ) if they previously answered that they were interested in weight-loss. If someone is not interested in losing weight, then the choices would not be perceived as rewards, therefore their answers would not accurately result in a delay discounting parameter for weight-loss rewards. The WCQ is an adaptation of the MCQ but instead using weight-loss rewards, for example – "Would you prefer to lose (A) 2.5 kg immediately, or (B) 3.4 kg in 61 days?" As our questionnaire was largely distributed amongst British participants, the monetary units in the MCQ where changed from dollars to pounds but with the same values (e.g. $55 became £55). The WCQ questions were also changed from lbs into kg, but the resulting kg amount was halved and rounded to the nearest half kilogram (e.g. 5.5 lbs became 2.5 kg).

Choices made in the WCQ and MCQ tasks were scored separately using a Python implementation of the hierarchical Bayesian methods outlined in Vincent (2016), using the MCMC sampling package PyMC3 (Salvatier et al., 2016). The hierarchical component of the scoring procedure acts to optimally estimate discount rates from the data, incorporating the knowledge that participants are drawn from a group. We took the posterior mean as the estimated discount rate for each participant. Because discount rates are known to be highly positively skewed, we report natural log discount rates for money and weight loss rewards ($\ln(k) = \log_e(k)$).

2.6 Discounting moderates rate of BMI gain hypothesis

Here we formally define our hypothesis that discount rates affect the rate of BMI gain per year (Figure 1, right). We know from Sutin and Ferrucci (2011) that there is a mild quadratic component, but lacking a very large number of older participants, we make the reasonable simplifying assumption of a linear increase in BMI with age, $BMI = \beta_0 + slope \cdot age$. We define this slope as a function of discount rate: $slope = \beta_1 + \beta_2 \cdot \ln(k)$. If we combine these equations then we get $BMI = \beta_0 + (\beta_1 + \beta_2 \cdot \ln(k)) \cdot age$. Simple rearrangement shows the equivalent model, $BMI = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot \ln(k) \cdot age$, which is more recognisable as a moderation analysis, without the main effect of $\ln(k)$. We formulate this into the following

Bayesian model:

$$\beta_0 \sim \text{Normal}(20, 10) \tag{1}$$
$$\beta_1 \sim \text{Normal}(5, 10) \tag{2}$$
$$\beta_2 \sim \text{Normal}(0, 10) \tag{3}$$
$$\sigma \sim \text{HalfNormal}(0.5) \tag{4}$$
$$\mu = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot \ln(k) \cdot age \tag{5}$$
$$BMI \sim \text{Normal}(\mu, \sigma) \tag{6}$$

We estimated $P(\beta_0, \beta_1, \beta_2, \sigma | age, \ln(k))$ using the MCMC sampling package PyMC3 (Salvatier et al., 2016). If our posterior over β_2 is credibly greater than zero then we have evidence that log discount rates moderate the rate of BMI gain per year. If the posterior over β_1 is credibly greater than zero then we have evidence that BMI increases with age. We conducted this analysis for $\ln(k_{\text{money}})$ and $\ln(k_{\text{weight}})$ separately. Note that for this analysis we define age in units of decades so that corresponding slope of the moderation effect, $slope = \beta_1 + \beta_2 \cdot \ln(k)$, is in units of BMI gain per decade, (kg/m^2)/decade. The β_1 parameter is in also in units of (kg/m^2)/decade.

Because we are operating with log transformed discount rates, $\ln(k)$ is unit-less, which means that β_2 is also a unit-less quantity. Therefore choosing an appropriate scale for the prior over β_2 is troublesome, and so we could not calculate a Bayes Factor for the hypothesis that $\beta_2 = 0$. Instead, we rely upon examining the posterior over β_2 and interpreting the practical significance of β_2 in terms of the rate of BMI gain per decade at the extremes of the moderator values.

2.7 Bayesian meta analysis

Our aim was to examine our findings in the context of relevant similar correlational studies, rather than to conduct a novel full meta analysis. Study inclusion is simple for the correlation between the WCQ and BMI as the only relevant studies are the present study and that by Lim and Bruce (2015). Study inclusion for monetary rewards was based upon the correlational studies included in the meta-analysis of Amlung et al. (2016). The following differences were made however. Firstly, we only include correlational studies. Secondly, we incorporate the correlational result from the present study. Third, where multiple measures of discount rates for money are given we take the most accurate. For example if an adaptive computer based discounting task was run as well as the MCQ, then we took the former only. Fourth, because discount rates for different commodities (e.g. money or food or weight loss) are not measuring the same thing, we only include correlations between discount rates for monetary rewards, not food rewards. We used these subtle deviations from Amlung et al. (2016) to maximise the similarity and compatibility of the studies included in the meta analysis. Effect sizes were reversed for studies reporting correlations between Area Under Curve (AUC; Myerson et al., 2001) measures and BMI to make them compatible with discount rates.

The Bayesian meta analysis as described below, run on studies reporting correlations between BMI and monetary discounting, was conducted with custom Python code written by B.V. The code and input data for the meta-analysis are available in the Supplementary Materials.

We can define a random effects meta analysis, where the study is the random effect. Given S studies we have lists of observed correlation coefficients $\mathbf{r}^{\text{obs}} = [r_1, \ldots, r_S]$ and sample sizes $\mathbf{n}^{\text{obs}} = [n_1, \ldots, n_S]$. We convert correlation coefficients into z-space with Fisher's transformation $z = F(r) = 0.5 \cdot \ln\left(\frac{1+r}{1-r}\right)$ (Fisher, 1915), resulting in a vector $\mathbf{z}^{\text{obs}} = [z_1^{\text{obs}}, \ldots, z_S^{\text{obs}}]$. If we want to infer the latent population level effect size, r, based upon observed study level effects ($\mathbf{r}^{\text{obs}}$) and sample sizes ($\mathbf{n}^{\text{obs}}$), then we can treat this as Bayesian hierarchical inference. To do this we defined the following probabilistic generative model:

$$r \sim 2 \times \text{Beta}(2,2) - 1 \tag{7}$$
$$\sigma_z \sim \text{HalfNormal}(0.5) \tag{8}$$
$$z_s^{\text{study}} \sim \text{Normal}(F(r), \sigma_z) \tag{9}$$
$$z_s^{\text{obs}} \sim \text{Normal}\left(z_s^{\text{study}}, \frac{1}{\sqrt{n_s^{\text{obs}} - 3}}\right). \tag{10}$$

We specify a mildly informative stretched Beta prior over the true population level correlation coefficient, r, which allows the data to dominate the final posterior distribution. This is a better option compared to a uniform prior as it incorporates our prior knowledge that extremely strong correlation coefficients are less probable then weaker correlation coefficients (Wagenmakers et al., 2018). We define individual studies to have a correlation coefficient in z-space, z_s^{study}, to vary around the true correlation coefficient in z-transformed space, $F(r)$. This study variability (in z-space) is captured by the latent parameter σ_z. The last equation defines the likelihood term where the observed correlation coefficients in z space z_s^{obs} are normally distributed around the inferred study z value, z_s^{study}. The standard deviation of the likelihood term, $1/\sqrt{n_s^{\text{obs}} - 3}$, comes from Fisher's transformation. This is important as it is responsible for 'weighting' studies in a principled manner by their sample size. Studies with larger sample sizes will have a greater influence upon the population level correlation coefficient r as we have higher measurement precision, and vice versa.

The study level variance parameter, σ_z, is an important parameter which describes the standard deviation of the true study level correlation coefficients from the true population level correlation coefficient. If $\sigma_z = 0$ then we have a special case where the random effects meta analysis is equivalent to a fixed effects meta analysis as it states that all true study level correlation coefficients are equal to the population level correlation coefficient r. In full, it equates to the following fixed effects meta analysis model:

$$r \sim 2 \times \text{Beta}(2,2) - 1 \tag{11}$$
$$z_s^{\text{obs}} \sim \text{Normal}\left(F(r), \frac{1}{\sqrt{n_s^{\text{obs}} - 3}}\right). \tag{12}$$

However, if $\sigma_z > 0$ then we have evidence that the study effect sizes are *not* measuring the same underlying effect size, r, and that there is some other source of variance. This could be caused by differences in participant composition of studies, or different methods of measuring discounting, or any number of reasons. We took the approach of running the random effects meta analysis, and examined the prior and posterior of σ_z to see if there was evidence for all the studies measuring the same underlying effect size or if there were additional study level variance. If so, this could be interpreted as some other (as yet unknown) source of variance meaning that the studies are *not* all measuring the same underlying effect size.

We evaluated $P(r, \sigma_z, \mathbf{z}^{\text{study}} | \mathbf{r}^{\text{obs}}, \mathbf{n}^{\text{obs}})$ for the random effects meta analysis (for discounting of money; Equations 7–10), and $P(r | \mathbf{r}^{\text{obs}}, \mathbf{n}^{\text{obs}})$ for the fixed effects meta analysis (for discounting of weight loss; Equations 11, 12) using MCMC sampling with the PyMC3 package (Salvatier et al., 2016). The resultant posterior distributions over the study level normalised correlation coefficients were transformed back into correlation coefficients using the inverse of the Fisher transformation $r_s^{\text{study}} = F^{-1}(z_s^{\text{study}})$ and are presented in Figure 5 as points with 95% highest density intervals (HDI). Reported correlation coefficients $\mathbf{r}^{\text{obs}}$ are shown as crosses. The posterior over r represents our degree of belief in the population level correlation coefficient, and is displayed in Figure 5 as the 'meta-analytic result'.

3 Results

3.1 Properties of the dataset

After participant exclusion (see Methods) we had a total of 381 participants (242 female, 139 male). Of these 257 (67.5%) reported being interested in weight loss. The BMI distribution was broad and positively skewed, representative of the broader population with 14 people (3.7%) severely underweight (BMI < 17.5), 11 people (2.9%) underweight (17.5 ≥ BMI < 18.5), 210 people (55.1%) normal (18.5 ≥ BMI < 25), 80 people (21.0%) pre-obese (25 ≥ BMI < 30), and 66 people (17.3%) obese (BMI > 30). Table 1 shows the correlations between continuous variables. Summary statistics and expanded analyses are available in the Supplementary Materials.

Table 1: Bayesian Pearson correlations, 2-sided tests using a uniform prior.

		Age	BMI	SFRS	$\ln(k_{\text{money}})$	$\ln(k_{\text{weight}})$
Age	Pearson's r	–				
	BF_{10}	–				
BMI	Pearson's r	0.451***	–			
	BF_{10}	2.838e+17	–			
SFRS	Pearson's r	0.412***	0.810***	–		
	BF_{10}	1.189e+14	1.722e+86	–		
$\ln(k_{\text{money}})$	Pearson's r	0.001	0.059	0.073	–	
	BF_{10}	0.064	0.125	0.175	–	
$\ln(k_{\text{weight}})$	Pearson's r	0.047	0.016	0.006	0.302***	–
	BF_{10}	0.103	0.081	0.078	13814.178	–

* $BF_{10} > 10$, ** $BF_{10} > 30$, *** $BF_{10} > 100$

3.2 Discount rates for money versus weight loss

Because discount rates are highly positively skewed, in line with common practice we calculated the natural log discount rates for both money, $\ln(k_{\text{money}})$, and weight loss, $\ln(k_{\text{weight}})$, from the MCQ and WCQ tests, respectively. We report and analyse $\ln(k_{\text{money}})$ values for all 381 participants, but because participants who indicated they were not interested in weight loss did not complete the WCQ, we report and analyse 257 $\ln(k_{\text{weight}})$ values.

How are the MCQ and WCQ scores relate to each other? A Bayesian 1-tailed test for a positive correlation between $\ln(k_{\text{money}})$ and $\ln(k_{\text{weight}})$ showed decisive evidence for a positive correlation ($BF_{+0} = 27,628$). However the effect size is small, with only around 9% of shared variance, $R^2 = 0.091$ ($\text{CI}_{95\%}$: $0.034, 0.166$), $N = 257$. This is in line with the findings of (Lim & Bruce, 2015) who report a Spearman's rank order correlation coefficient of 0.33 ($R^2 = 0.109$).

We explored this low level of shared variance further by testing whether there were linear predictors of the ratio between discount rates, $\ln(k_{\text{weight}})/\ln(k_{\text{money}})$. In short, there was convincing evidence that sex, age, BMI or various interactions are not related to the ratio between discount rates for weight loss and money (see Supplementary Materials).

3.3 Effects of age

Based on a Bayesian ANCOVA, there was decisive evidence ($BF_{10} = 2.395 \times 10^{17}$) for a main effect of age upon BMI (see Figure 2; further details in the Supplementary Materials) in line with the results of Sutin and Ferrucci (2011). Because of this relationship between age and BMI,

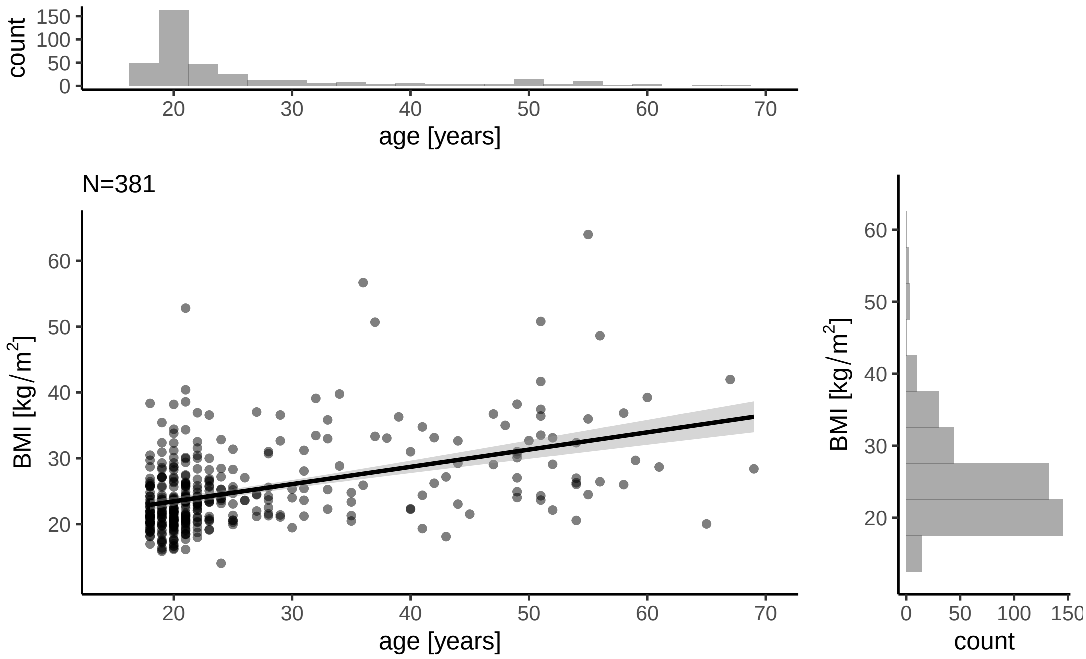

Figure 2: Relationship between BMI and age. Approximately 20% of the variance in BMI can be accounted for by age (R^2 = 0.203, see Table 1).

we argue below that it is important for studies exploring the relationship between discounting and BMI to account for the effect of age (e.g. Figure 1 middle, right).

Age did not predict either $\ln(k_{\text{money}})$ or $\ln(k_{\text{weight}})$. A Bayesian linear regression of age upon $\ln(k_{\text{money}})$ showed moderate evidence against a main effect of age ($BF_{01} = 8.834$). This was also the case for $\ln(k_{\text{weight}})$, with moderate evidence for the null model $BF_{01} = 5.606$.

3.4 Does discounting predict BMI?

Taking the simple correlation approach (e.g. Figure 1, left), we examined whether discount rates for money or weight loss are able to predict the real-world health outcome of BMI. The results are visualised in Figure 3 (top row) and essentially show that the answer is 'no'. To test this quantitatively we can first see that the Pearson regression coefficient (see Table 1) between $\ln(k_{\text{money}})$ and BMI is only 0.059 with evidence *against* there being a correlation ($BF_{10} = 0.125$). In other words the hypothesis that there is no relationship becomes $1/0.125 = 8$ times more credible after having observed the data compared to our beliefs prior to observing the data. This counts as moderate evidence against a correlation.

A similar result occurs for discounting of weight loss – the Pearson regression coefficient (see Table 1) between $\ln(k_{\text{weight}})$ and BMI is only 0.016 with evidence *against* there being a correlation ($BF_{10} = 0.081$). In other words the hypothesis that there is no relationship becomes $1/0.081 = 12.35$ times more credible after having observed the data. This counts as strong evidence against a correlation.

We also tested for main effects of and an interaction between $\ln(k_{\text{money}})$ and $\ln(k_{\text{weight}})$ in predicting BMI. The null model was the best account of the data – there was significant (or stronger) evidence against the main effect or interaction models (see Supplementary Materials for full details).

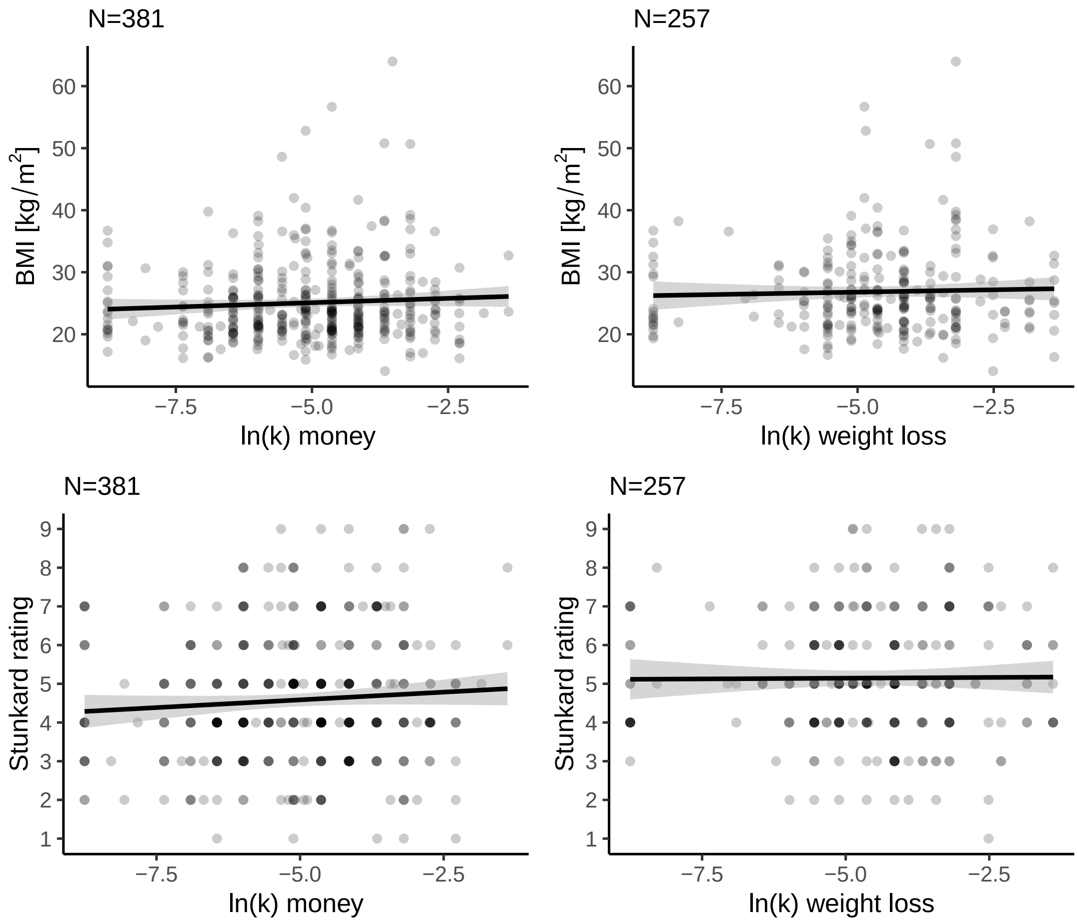

Figure 3: Lack of relationship between discounting of money (left column) or weight loss (right column) and BMI (top row) and Stunkard scores (bottom row).

3.5 Does discounting predict BMI when taking age into account?

Because of the strong relationship between age and BMI, we argue that age should be taken into account when looking for a relationship between discounting and BMI. We did this under the main effect approach of Figure 1 (middle) by testing for main effects of age and discount rates. More specifically a Bayesian linear regression was run with BMI as the outcome variable and age, $\ln(k_{\text{money}})$, and $\ln(k_{\text{weight}})$ as predictors. The best model was a main effect of age only. There was anecdotal evidence against additional main effects of $\ln(k_{\text{money}})$ ($BF_{01} = 2.05$) or $\ln(k_{\text{weight}})$ ($BF_{01} = 2.71$), and moderate evidence against the additional main effects of both $\ln(k_{\text{money}})$ and $\ln(k_{\text{weight}})$ ($BF_{01} = 5.29$). In summary, there is some evidence against discount rates of money and/or weight loss being a main effect of BMI even when age is taken into account.

3.6 Does discounting predict a rate of BMI gain per year?

We hypothesised that discount rates may moderate the rate at which BMI increases with age (Figure 1, right). These analyses were conducted separately for discounting of money and weight loss, and in short there was evidence for BMI increasing with age, but against discounting (of either money or weight loss) as moderators of rate of BMI gain.

The moderation effect of $\ln(k_{\text{weight}})$ upon the rate of BMI gain with age was unambiguously absent. The slope of the moderation effect, β_2 had a mean of 0.001 ($\text{HDI}_{95\%}$: $-0.182, 0.180$), in units of per decade.

The moderation effect of $\ln(k_{\text{money}})$ upon the rate of BMI gain with age was also near absent, however we show results of this analysis in Figure 4. The slope of the moderation effect, β_2 had a mean of 0.096 ($\text{HDI}_{95\%}$: $-0.024, 0.216$), in units of per decade. So while the 95% highest density intervals overlap with zero, 94% of the probability mass was greater than zero. So in order to more thoroughly investigate this we examine the effects of the lowest versus the highest $\ln(k_{\text{money}})$ values upon the rate of BMI gain with age. Figure 4 (top left) shows that the lowest discounters gain about 2 BMI units per decade whereas the highest discounters gain about 3 BMI units per decade. While this is interesting, the practical consequence of this is negligible – making some reasonable assumptions, this means that people with the highest discount rate will gain only 0.35kg more *per decade* than a person with lowest discount rate. That is, according to our data, over a 10 year period someone with the highest discount rate will gain the physical weight of approximately 9 doughnuts more than someone with the lowest discount rate[1]. We argue that the practical significance of this is near zero, and conclude that discounting of monetary rewards does not moderate the rate of BMI gain with age.

3.7 Does discounting predict Stunkard ratings?

Figure 3 (bottom row) shows the relationship between discount rates and subjective body image as measured by the Stunkard Figure Rating Scale. To explore what if anything could predict these Stunkard ratings, we conducted a Bayesian ANCOVA with the Stunkard rating as the outcome variable, sex as a fixed factor, and $\ln(k_{\text{money}})$ and $\ln(k_{\text{weight}})$ as predictors. The best model was the null model, with no clear evidence of any important predictors of the SFRS score. Bayes Factors for all models are presented in the Supplementary Material.

3.8 Meta-analytic findings for the discounting of money and BMI

Taken in isolation, our empirical findings provide unambiguous evidence against either $\ln(k_{\text{money}})$ or $\ln(k_{\text{weight}})$ being related to BMI or rate of BMI gain per year. This is consistent with the

[1]The average yeast-raised doughnut weights 38g, so 350g/38g = 9.2.

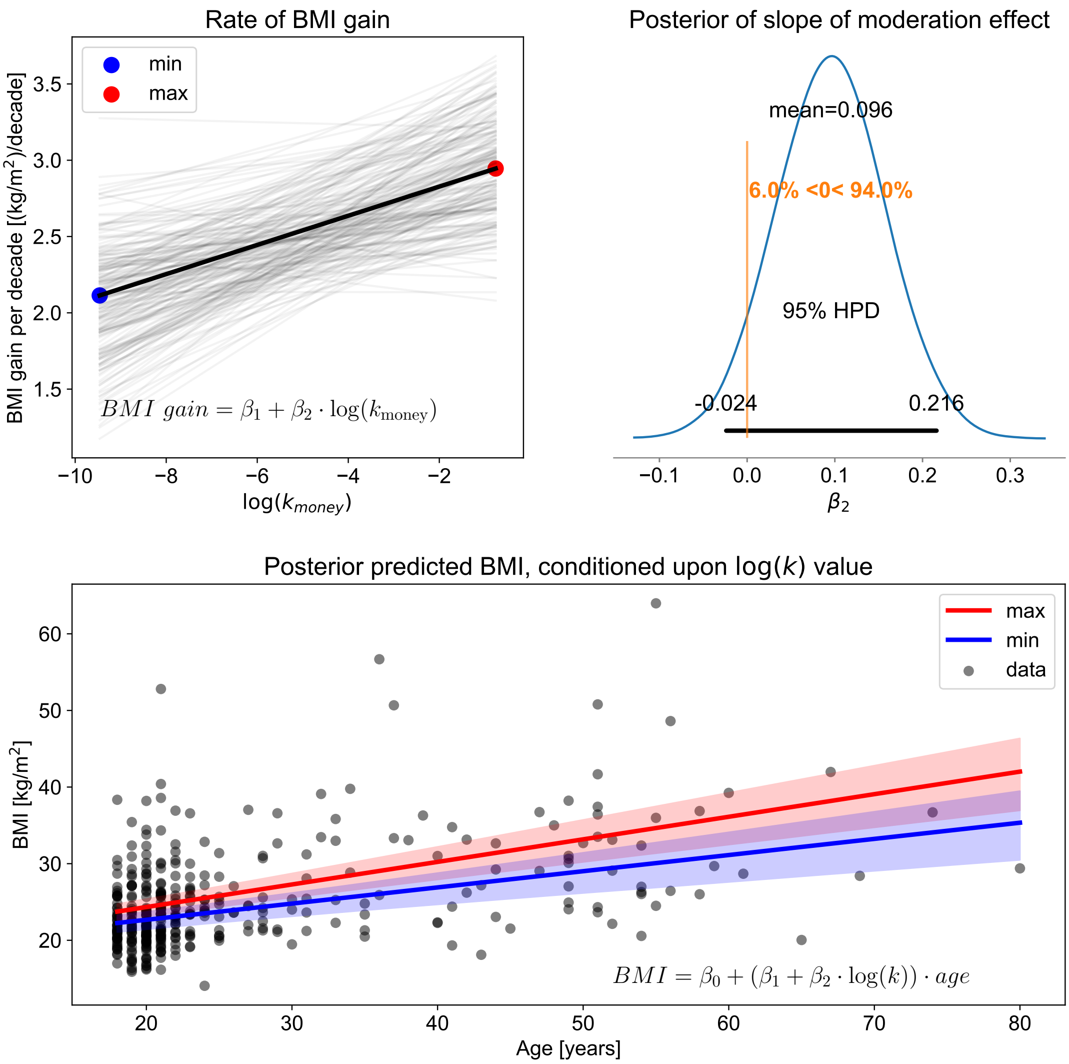

Figure 4: Evaluating the hypothesis that discounting (of money) influences the rate of BMI gain with age. There is some evidence for an effect of discount rate on the rate of BMI gain (top left, top right). The 95% credible interval of the posterior over the β_2 parameter overlaps with zero, however 94% of the probability mass is greater than zero. The effect upon the rate of BMI is shown (bottom left) as the difference in the slopes of those with either the minimum or maximum discount rates in our dataset (red and blue lines, respectively). The difference in slopes is not very large, see main text. The β_2 parameter is a unit-less quantity.

findings of Lim and Bruce (2015), which was the only previous study to correlate the WCQ score against BMI. However, there is considerable variation in reported correlation coefficients between $\ln(k_{money})$ and BMI in the literature. We therefore sought to gain further insights about how to interpret our empirical results in the context of the wider literature by computing some meta-analytic estimates. Our meta-analytic estimates were based upon a recent meta analysis conducted by Amlung et al. (2016). Because of significant concerns about study heterogeneity raised by previous meta analyses, here we focus only upon studies with correlational designs. We avoid studies with case-control designs in order to reduce concerns about study heterogeneity from conducting assumption-laden effect size conversions.

Results of a Bayesian random effects meta analysis (Figure 5) showed a small inferred true effect size (Pearson's correlation coefficient): $R = 0.15$ [$\text{HDI}_{95\%}$: 0.07, 0.22]. That is, the R^2 value suggests that $\ln(k_{money})$ can explain only 2.25% of the variance in BMI [$\text{HDI}_{95\%}$: 0.49%, 4.84%].

To quantitatively evaluate the point hypothesis (that there is no correlation, $r = 0$), we calculated a Bayes Factor. This resulted in a score of $BF_{10} = 21.08$, meaning that our belief in the correlation being zero *decreases* by approximately 21 times after having observed the effect sizes included from the literature. Taken at face value, this is strong evidence for a correlation between monetary discounting and BMI, albeit with a small effect size.

However, it is important to not take this at face value. Because we conducted a random effects meta analysis, we also have posterior estimates about study-level variability, σ_z. If $\sigma_z = 0$ then this would indicate that the studies entered into the meta-analysis are homogeneous in that they could be considered as independent measurements of the same underlying population coefficient. However, if $\sigma_z > 0$ then we would have evidence for study heterogeneity, that each of the studies are *not* measuring the same underlying population coefficient. We find extremely strong evidence for the latter – Figure 6 shows that the prior belief that $\sigma_z = 0$ drops to zero in the posterior, equating to an infinite Bayes Factor that $\sigma_z > 0$. Therefore, we have extremely strong evidence that even though we restrict ourselves to correlational study designs reporting discounting behaviour or monetary rewards, these reported effect sizes are *not* independent measurements of the same population level correlation coefficient. That is, the studies are not all measuring the same thing[2]. Put another way, there is overwhelming evidence for some additional source of variability across studies which is as yet unaccounted for. The Discussion explores what these possible sources of variability may be, and how this should influence our interpretation of what our meta-analytic result is telling us.

3.9 Meta-analytic findings for the discounting of weight loss and BMI

While there are only 2 studies (the present study and Lim & Bruce, 2015) which have examined discounting with the WCQ and BMI, it is worth examining what we should believe about a relationship between k_{weight} and BMI. A Bayesian fixed effects meta analysis (see Methods) was conducted as there are not enough studies to accurately estimate σ_z.

There was evidence against the presence of a correlation (see Figure 7). The estimated true effect size was small, with broad confidence intervals which encompass zero, $R = 0.07$ [$\text{HDI}_{95\%}$: -0.03, 0.19]. The Bayes Factor was $BF_{01} = 4.26$ which counts as moderate evidence in favour of no effect. While this is not promising in terms of a link between discounting of weight loss and BMI, refining this estimate with additional studies is certainly warranted.

[2]We do not make any claims about study heterogeneity of studies using case-control designs included in the meta analysis of Amlung et al. (2016)

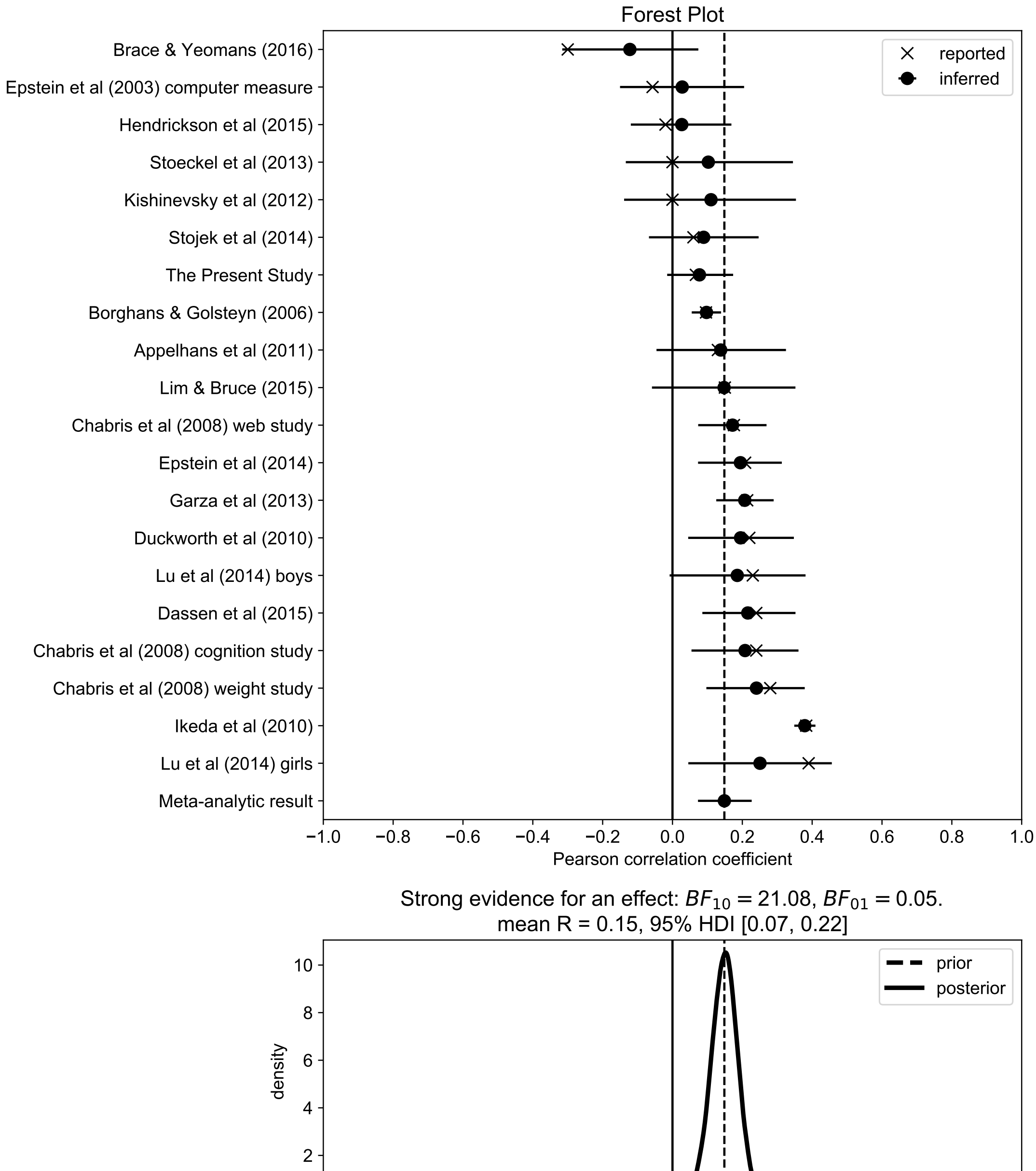

Figure 5: Bayesian random effects meta analysis of studies reporting Pearson correlation coefficients of discounting with age. Top panel shows the forest plot of studies. Reported correlation coefficients are shown by crosses. Inferred true correlation coefficients (and 95% Highest Density Intervals) are shown by black points (posterior mean) and error bars (95% Highest Density Intervals). The bottom panel shows the prior (dashed line) belief over effect size as well as the posterior beliefs after having observed the data (solid line).

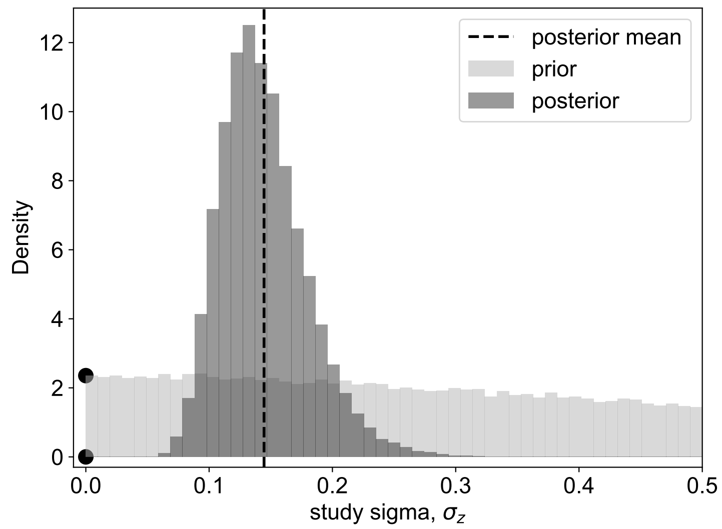

Figure 6: Extreme evidence for study-level variability in the $\ln(k_{\text{money}})$ random effects meta analytical result shown in Figure 5. The posterior density for the $\sigma_z = 0$ is zero, meaning that the prior belief that $\sigma_z = 0$ has decreased by an infinite amount after having observed the study level correlation coefficients (shown by points). The posterior mean (dashed line) is equal to 0.145, and note that this is the standard deviation in Fisher's transformed space.

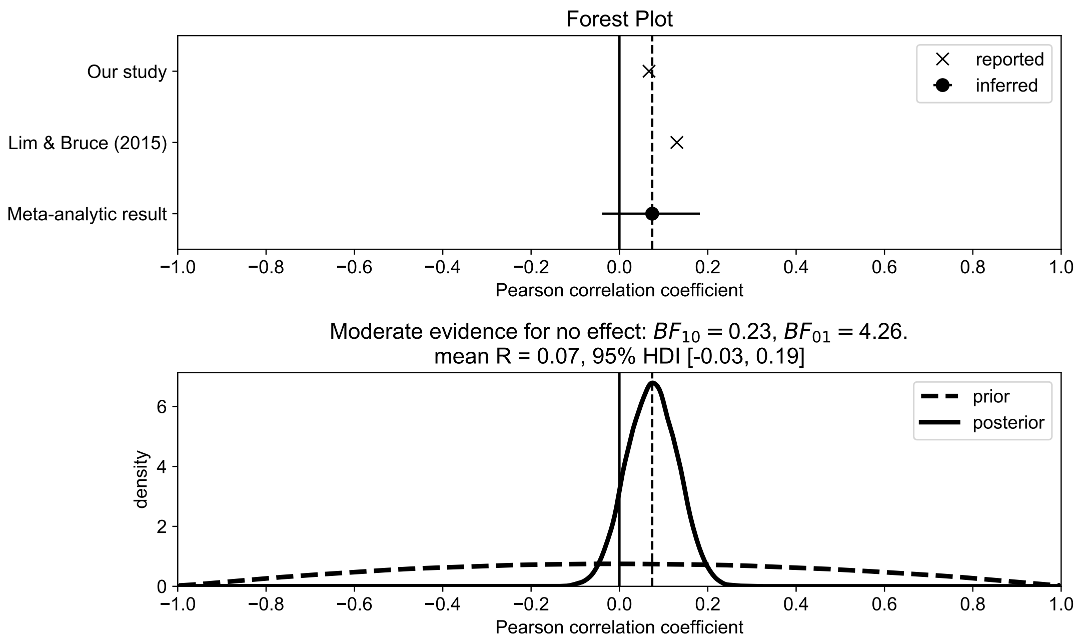

Figure 7: Bayesian fixed effects meta analysis of studies correlating discount rates of weight loss with BMI. Explanation as in Figure 5.

4 Discussion

4.1 Empirical findings

We collected a large dataset of $N = 408$ responses using online survey methods from unpaid and therefore intrinsically motivated participants. To ensure the data were reliable, we used strict inclusion criteria including a threshold on the number of responses correctly predicted by hyperbolic discount functions using Bayesian parameter estimation (Vincent, 2016). This resulted in a total of $N = 381$ participants.

Our results support Lim and Bruce's finding that monetary and weight-loss discount rates showed a positive correlation - and we support the use of the WCQ to measure discounting of weight loss rewards. The shared variance (R^2) is low however, meaning that we discount somewhat differently for weight-loss rewards than monetary rewards, supporting the theory of domain-specific discounting (e.g. Emery & Levine, 2017). The idea that impulsivity is not a unidimensional construct demonstrates the importance of domain-specific discounting measures, and the need for a measure that is specifically related to weight-loss when exploring factors of impulsivity in obesity research. This supports the basis of the WCQ as a useful tool to measure distinct impulsigenic traits related to weight management. We were unable to find any variables in our dataset which predicted the relative discount rates of money versus weight loss, and so the relative desire for immediate money or weight loss has yet to be explained.

Based on mixed findings in the literature we examined whether age was a predictor of discount rates – we found moderate evidence *against* a linear trend in discount rates as a function of age. This is consistent with Green, Myerson, and Ostaszewski (1999) who found no relationship between age (in adulthood) and discount rates, but inconsistent with Green, Fry, and Myerson (1994), Steinberg et al. (2009), and Green et al. (1999) who report some either linear or non-linear relationships between age and discount rates. Given that our research question was not targeted specifically at addressing a possible age-discounting relationship, and the age distribution of our sample, we consider these as preliminary findings.

There was decisive evidence however for a linear increase in BMI with participant age. This is known from previous work such as Sutin and Ferrucci (2011), so this seems a robust observation and motivated our proposals for alternative ways of linking discounting and BMI (Figure 1, middle, right). The fact that age was the only credible predictor of BMI in our dataset does suggest that age is a particularly important factor when looking at the discounting/BMI relationship.

In terms of the basic correlation approach (Figure 1, left), between discounting and BMI, our empirical results show moderate evidence against discounting for money being predictive of BMI ($r = 0.059$ [$\text{CI}_{95\%}$: $-0.041, 0.158$], $BF_{01} = 7.997$), and strong evidence against discounting for weight loss being predictive of BMI ($r = 0.016$ [$\text{CI}_{95\%}$: $-0.106, 0.137$], $BF_{01} = 12.391$). By using Bayesian analysis methods we are able to make claims of what we care about, which is the level of evidence for our hypotheses. Our results are in line with the findings of Lim and Bruce (2015). However their interpretation was that there may well be a correlation between discount rates and BMI, but that their low sample size meant that this was not detected. Our interpretation differs – given our much larger sample size, similarity of results, and use of Bayesian methods, the only credible conclusion we can draw from the data is that there is no relationship between discounting (of money or weight loss) and BMI. We did not measure discount rates for food rewards, so our data cannot speak to a possible relationship between that and BMI.

We found no evidence for a main effect of discounting in our 'main effect' model (Figure 1, middle). We found the best explanation is that age linearly predicted BMI. There was moderate evidence against the additional main effect of $\ln(k_{\text{money}})$, and extreme evidence against an additional main effect of $\ln(k_{\text{weight}})$.

We also found no evidence that discounting (of money or weight loss) moderated the rate of BMI gain with age (Figure 1, right; Figure 4). Despite this, we suggest that it may still be worth evaluating this rate of BMI gain model with an even larger sample size with a more balanced age distribution. We also cannot say anything about how the rate model would fair if measuring discounting of food rewards – so this is an interesting open question. We also suggest that it could be fruitful to consider this or related process models. For example, it may be useful to more carefully examine how discounting relates to energy-in and energy-out behaviours such as eating (Appelhans et al., 2012) and exercise (Albelwi, Rogers, & Kubis, 2019), respectively.

In addition to the objective measure of BMI, we also tested the hypothesis that discounting might be predictive of subjective self-perceived BMI through the SFRS scale. We found evidence against this hypothesis, with the only meaningful predictor of SFRS ratings being sex. On average women reported marginally higher SFRS scores than men. The evidence supported no role for discount rates in the SFRS scores.

4.2 Limitations of empirical findings

Our choice to use questionnaire methods enabled a large sample size, but potentially gave rise to more noisy measures. While our participants were unpaid, and therefore arguably self-motivated, we attempted to limit noise as much as possible by relatively strict inclusion criteria. However, a potential issue could arise from our BMI measure – in comparison to accurate lab-based measures, self-reported height is often overestimated in men and weight underestimated in women (Brener, McManus, Galuska, Lowry, & Wechsler, 2003; Gosse, 2014; Maukonen, Männistö, & Tolonen, 2018; Shiely et al., 2010; Wen & Kowaleski-Jones, 2012). However, the differences between self-reported and actual BMI is small, normally within 1 BMI-unit. Considering Shiely et al. (2010) and Wen and Kowaleski-Jones (2012) do not record self-reported BMI and actual BMI on the same day, this difference may in part be a result of everyday body weight fluctuations, as we fluctuate around 2kg every day due to things like food and water intake, bowel movements, hormone levels — enough to alter 1 BMI-unit. These studies also show that unreliability in self-reported BMI increases as BMI increases. This suggests that the issue is likely to lie in social desirability factors, as stigma against overweight individuals and cultural fixation on thinness may lead people to be embarrassed about having a high BMI, and a desire to under-report it. The anonymous nature of our questionnaire may have limited self-report bias by removing any component of social desirability. Completing the survey online also provides another layer of anonymity, encouraging people to tell the truth more than if they completed the survey in person, such as in Brener et al. (2003). Whilst completing their weight and height first may give subtle demand effects for the following WCQ survey, asking these measures first increases the chance that people won't alter their weight after the WCQ has encouraged them to think about weight loss, again helping to reduce social desirability effecting the BMI scores. However, self-reported BMI may have issues other than social desirability influence, such as uncertainty on whether standardised measures were used by participants, so we must acknowledge the possibility of measurement error in this study. However, we believe it is not substantial enough to invalidate the findings – Bolton-Smith (2000) and Olfert et al. (2018) concluded that self-reported height and weight is an acceptable and accurate way to measure BMI and monitor obesity. Amongst studies in the meta-analyses discussed previously (Amlung et al., 2016; Emery & Levine, 2017; McClelland et al., 2016), self-reported BMI studies have shown both correlations and no correlations, and in-person studies have shown both correlations and no correlations, suggesting that the discrepancies across the literature transcend methodological differences in BMI measurement.

The methods used to estimate discount rates are also a potential limitation. While there are adaptive methods which give rise to more precise estimates (Du, Green, & Myerson, 2002;

Frye, Galizio, Friedel, DeHart, & Odum, 2016; Vincent & Rainforth, 2018), these are currently not implemented in online internet based questionnaire settings, hence the reliance upon the simple fixed set of non-adaptive choices in the MCQ and WCQ. The penalty paid however is two-fold. Firstly, while the measurement of discount rates are robust, in terms of relatively high test-re-test reliability (Kirby, 2009; Simpson & Vuchinich, 2000), fixed questionnaire methods inevitably has lower measurement precision compared to adaptive approaches. Secondly, it is only sensitive to a limited range of discount rates. This floor and ceiling effect is revealed in how some participants answer the immediate reward for all the questions, or the delayed reward for all the questions. While we cannot rule out the possibility that higher measurement precision of discount rates (or BMI) would have demonstrated a relationship between discounting and BMI, we have employed well-used and established methods used in many other studies exploring the relationship between discounting and BMI. Going forward, using adaptive discounting procedures with higher measurement precision would be advantageous.

4.3 Meta-analytical findings

While our empirical results, with a relatively high N, clearly provide evidence for *lack* of a correlation between discount rates and BMI, the findings from our meta-analytic result paint a more complex picture. On the face of it, the meta-analytic result is quite clear in suggesting that there is strong evidence ($BF \approx 29$) for a non-zero correlation coefficient, but that this is a small effect, with a correlation coefficient of 0.15 [$\text{HDI}_{95\%}$: 0.07, 0.23]. However, meta-analyses must be interpreted cautiously, especially when there is a high degree of study heterogeneity (Thompson & Pocock, 1991). We should take into account two main things however before concluding that there is an effect.

The first is if the effect size is this small, then what is the practical consequence in the real world? If discounting for money can only explain 2.25% of the variance in BMI, does this represent an exciting or clear causal connection that we should continue to study? It is important to note that a low (or zero) correlation does not prove a lack of a causal connection – a direct or indirect causal connection could still be present, but masked due to not having measured relevant additional variables nor understanding their varied causal interconnections. But it does behove the proponents of a link to more fully outline what a causal connection might be. In this paper we made an attempt at this by exploring the hypothesis that discounting influences (unobserved) behaviours that influence a rate of BMI change over time – but we found evidence against this hypothesis.

The second important aspect of the meta-analytical result to take into account is that there was essentially infinite evidence that we have unaccounted for study-level variance. That is, even just taking the correlational studies from the published literature, there is clear evidence that the reported correlation coefficients are *not* all independent measures of the same underlying correlation. Where does this study-level variation come from? We do not have answers here, but candidates would be: a) differences in methods used to measure discount rates, b) reporting discounting in AUC, or k, or $\ln(k)$, c) measuring height and weight in a lab setting versus self-report, d) differences in the composition of participants in smaller N studies. This study heterogeneity has been explicitly highlighted as problematic in previous meta analyses (Amlung et al., 2016; Emery & Levine, 2017; McClelland et al., 2016; Tang et al., 2018).

4.4 Ways forward

We have a radical disconnect between elegant predictions of discounting models, and empirical observations. On the one hand, hyperbolic discounting (or similar) offers a theoretical model which we may understand behaviours which are incongruent with long term weight-loss goals, for example, as being the result of high discount rates. On the other hand, we have multiple meta-analytical results suggesting that the correlation between discounting rates for monetary rewards is only marginally associated with BMI. While this is only the second study to explore the same for discounting for weight loss rewards, there is no clear cut evidence to suggest a compelling relation between these variables. We offer a number of possible ways forward.

Firstly, we suggest that future empirical efforts to resolve this should focus on quality and comparability – we need to get to a point where study level variance is low so that we have faith that the results of aggregating over studies actually means something.

Secondly, there is absolutely no reason to believe that BMI would be wholly determined by discount rates. Weight management relies on a multitude of self-control decision making processes, including resisting temptation of immediate pleasure from calorie-dense treats, to obtain long-term rewards of health management (Sze, Slaven, Bickel, & Epstein, 2017). The most successful and sustainable weight-loss involves long-term goals that can be impeded by impulsive choices and the desire for immediate results (Artinian et al., 2010; Hall et al., 2012). Therefore, we suggest that a useful empirical way forward would be to record as many plausibly useful predictors of BMI as possible, and to examine how these combine to predict BMI either in a linear or non-linear manner.

Third, we may need to go beyond correlating hyperbolic discount rates with BMI. It might be informative to further examine how discount rates affect both energy-in processes (Appelhans et al., 2012; Rollins, Dearing, & Epstein, 2010) as well as energy-out processes (Albelwi et al., 2019) separately. Further, Price, Higgs, Maw, and Lee (2016) suggest that moving from the 1-parameter hyperbolic discount function to dual-parameter discount functions may shed light on sub-processes of delay discounting which vary in obese and non-obese participants. But even this may not be enough – in their review, Story, Vlaev, Seymour, Darzi, and Dolan (2014) argue from a reinforcement learning framework that goal-incongruent actions can be triggered by factors that are unrelated to discount rates, such as temptations that arise in the environment and changes in motivational state.

Fourth, the more robust relationship between discounting and BMI in studies with a case-control design (compared to a correlational design) (e.g. Amlung et al., 2016) suggests a speculative resolution. Other meta analytic results suggest that discounting in people with bulemia nervosa, binge-eating disorder, or anorexia nervosa are associated with significantly different discount rates compared to controls (Amlung et al., 2019; McClelland et al., 2016). If participants in case-control designs are more likely to be suffering from an eating disorder than those in correlational studies, then perhaps the presence of an eating disorder is an explanatory 'third variable' which may be causing a spurious correlation between discount rates and BMI.

Fifth, is it unlikely that discount rates are the ultimate cause of behaviours influencing BMI and so we might need to reflect upon the possible causal direction of any association between discounting and BMI. For example, discount rates have been shown to change, both by an experimentally induced hunger manipulation (Skrynka & Vincent, 2019), and from an exercise intervention (Sofis, Carrillo, & Jarmolowicz, 2017). Evidence from a study in rats with diet-induced-obesity showed *decreases* in their discount rates (Robertson & Rasmussen, 2017), in line with other evidence (see studies discussed by Robertson & Rasmussen, 2017) that diet-induced obesity alters reward processing through the dopaminergic system. Overall we suggest the field explore more causal or process models, considering bi-directional or dynamic relationships.

4.5 Conclusion

In conclusion, we present a study with $N = 381$ with strict inclusion criteria. Our Bayesian analyses affords us the ability to conclude that we have direct evidence against the hypothesis that discounting for money or weight loss is related to BMI. We also found evidence that discounting was not correlated with a subjective measure of body mass as measured by the Stunkard Figure Rating Scale. In terms of the WCQ measure, while the notion that impatience for weight loss might drive counter-productive dieting strategies and thus higher BMI is interesting. But again, there is no strong evidence for this currently. Overall, while the notion that high discount rates might drive behaviours associated with higher BMI is appealing, we argue that on balance there is no strong evidence that this is true. Our results do not speak, however, to a possible connection between discounting of food rewards and BMI.

We present a meta-analytic result which superficially does suggest the presence of a small correlation between discount rates and BMI. However, we conclude that a) this is such a small effect size so as to be of questionable utility, and b) the meta-analytical result should be interpreted with extreme caution due to the study-level variance, probably caused by heterogeneity in study methods. We also find evidence against discount rates (of monetary or weight-loss rewards) moderating the rate of BMI gain with age. We have presented a number of recommendations as ways forward which we hope will be taken up by other researchers.

5 Acknowledgements

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6 Competing interests

The authors declare no competing interests.

7 Appendix

All data and code is available from the Open Science Foundation, https://osf.io/ncmf5/.

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